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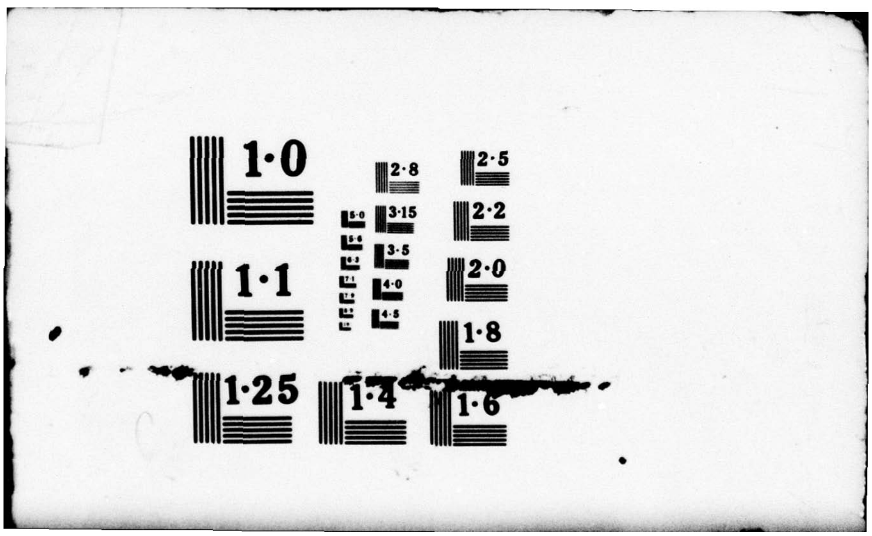
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A STATISTICAL RATIONALE FOR RELATING SITUATIONAL ATTRIBUTES AND INDIVIDUAL DIFFERENCES

Robert G. Demaree, Lawrence R. James, and John J. Hater

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Statistical rationale is presented for relating specific situational variables (e.g., technological complexity) to individual difference variables, or person variables (e.g., environmental perceptions, attitudes). A disaggregation procedure is described wherein unstandardized/standardized regression weights are determined for the regression of a person variable on one or more situational variables. The results of the procedure provide opportunities to ascertain (a) the degree to which variation among individuals on a person

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variable is associated with situational differences, and (b) the degree to which a situational variable accounts for the total possible variation in the person variable that is associated with situational differences. An important difference between unstandardized and standardized regression weights is noted, and an empirical illustration is presented.

Summary

Statistical rationale is presented for relating specific situational variables (e.g., technological complexity) to individual difference variables, or person variables (e.g., environmental perceptions, attitudes). A disaggregation procedure is described wherein unstandardized/standardized regression weights are determined for the regression of a person variable on one or more situational variables. The results of the procedure provide opportunities to ascertain (a) the degree to which variation among individuals on a person variable is associated with situational differences, and (b) the degree to which a situational variable accounts for the total possible variation in the person variable that is associated with situational differences. An important difference between unstandardized and standardized regression weights is noted, and an empirical illustration is presented.

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A STATISTICAL RATIONALE FOR RELATING SITUATIONAL ATTRIBUTES AND INDIVIDUAL DIFFERENCES

The primary objectives of this report are (a) to present a case favoring the development of measures of specific situational (environmental) attributes, and (b) to propose a statistical rationale for relating specific situational attributes with individual differences. Attention to these issues is needed inasmuch as the interface between situations and individuals who live, work, and otherwise experience those situations has received increasing attention (cf. Endler & Magnusson, 1976). One of the salient questions in this area is the degree to which individual differences (e.g., perceptions, attitudes, behaviors) are associated with differences among the situations. Efforts to provide answers to this question are frequently based on "between-group" analyses, where membership in a particular situation (e.g., workgroup, organization, residential area, treatment facility) is used as the independent variable (dummy variables in multiple regression, classification factors in ANOVA), and scores on an individual difference variable, or person variable (PV), are employed as the dependent variable. Using various forms of the general linear model, an estimate of variance accounted in the PV by "group membership" (e.g., membership in different organizations) is reported in the form of an eta-square, omega-square, intraclass correlation, or squared multiple correlation.

While this type of analysis reflects the amount of variation in the PV associated with group membership, it is also the

case that the independent variable -- group (situation) -- is typically quite global. Consequently, while the researcher knows that scores on the PV vary as a function of group membership, he/she may be unable to explain meaningfully, and with empirical support, specific aspects of the situations represented that are associated with the variations in the PV (James & Jones, 1976).

To illustrate, a critical question in research on perceived work environments, or perceived climate, is the degree to which individuals' perceptions of their environments (the PV) are related to situational attributes (cf. James & Jones, 1974). For example, suppose data on a PV such as perceived job challenge are available for 1,000 employees. Suppose further that each employee is a member of one formal workgroup, where (a) the number of workgroups is 100, (b) the average workgroup size is 10, although the workgroups range in size from 5 to 15, (c) the workgroups are assigned heterogeneous functions (e.g., manufacturing, accounting, marketing, research, and so forth), and (d) the members of each workgroup perform essentially the same tasks. The approach typically employed to ascertain whether the perceptions of job challenge are related to situational attributes is to conduct a one-way ANOVA, where workgroup ($\underline{i}$ = 1 ... 100) is employed as the between-group designator (cf. James, Hater, Gent, & Bruni, 1978). The resulting eta-square ($\underline{\eta}^2$), or alternatively an omega-square or intraclass correlation, is used as an indicator of the amount of variance in the job challenge perceptions that is associated with

workgroup differences. In a few cases, workgroups are collapsed into "functional specialities" (e.g., manufacturing, accounting, marketing, etc.), and functional speciality becomes the between-group designator.

To continue the illustration, it is assumed that the ANOVA using the 100 workgroups as the between-group designator provides an $\underline{\eta}^2$ of .20. This suggests that 20% of the variation in the job challenge perceptions is associated with differences among workgroups. But, to what is this variance to be attributed? The workgroups may vary with respect to level of technology, goals, size, division of labor, centralization of decision-making, leadership processes, communication processes, and physical environment -- to name a few situational attributes. Moreover, variation in the perceptions might not be limited to strictly situational attributes; that is, some part of between-group variation might reflect group differences in age, education, experience, and so forth. Clearly, a global indicator such as "workgroup" provides only the most rudimentary basis for explaining variation in the perceptions among workgroups. In general, the same conclusion is applicable to between-group designators such as functional specialization, where again it is usually the case that empirical assessments of relevant situational attributes (e.g., technology) and individual attributes (e.g., education) are not obtained[1].

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[1]Measures such as age, education, and experience are also person variables. However, in the present context these measures are regarded as predictors or perhaps control variables (covariates). Consequently, they will be referred to as individual attributes, and the term person variable will be reserved for the dependent, individual difference variable.

A meaningful solution to the problem introduced above can be initiated by identifying and then measuring specific situational and individual attributes that presumably are associated with between-group variation in the PV. The present discussion focuses on the need to measure specific situational attributes, but notes later that measures of individual attributes such as education may also be required. For example, on the basis of observation, interviews, literature reviews, and the like, it is decided that "complexity of the workgroup technology" should be associated with individuals' perceptions of job challenge (e.g., higher levels of technological complexity are associated with jobs perceived as more challenging). Suppose that a technological complexity scale is developed, for which a score of 10 represents high technological complexity and a score of 1 connotes low technological complexity. A measure of technological complexity is then obtained for each of the 100 workgroups. The computation of a relationship between (workgroup) technological complexity and (individual) perceptions of job challenge may be obtained in several ways. However, the question of primary concern is the relationship between the situational attribute and individuals' perceptions of job challenge -- that is, the desired level of analysis is the individual; and it is desired to maximize the power of the statistical analysis by employing parametric analytic procedures.

For these reasons, the relationship between technological complexity and perceptions of job challenge can be determined by the following steps. First, the workgroup scores on

technological complexity are "disaggregated" to the individual level of analysis. This is accomplished by assigning the technological complexity score for each workgroup to every individual in that workgroup. That is, all individuals in the same workgroup receive the same score on technological complexity. By this procedure the technological complexity scores assigned to individuals will vary among individuals from at least some <u>different</u> workgroups unless all workgroups receive the same score on technological complexity.

The second step is simply to determine the unstandardized regression weight or standardized regression weight that relates (disaggregated) technological complexity to perceptions of job challenge. It is crucial to note that the unstandardized/standardized regression weight is determined on the sample of 1,000 individuals. To continue again with the illustration, assume that the standardized regression weight, or correlation ($\underline{r}$) in the bivariate case, is .30. This suggests that 9% ($\underline{r}^2$) of the variance in individuals' perceptions of job challenge is associated with (note -- not necessarily caused by) the technological complexity of workgroup functions. Clearly, this information is superior to the information provided by the between-groups analysis because we now have a partial basis for attempting to explain what it is about workgroup environments that is associated with perceptions of job challenge. However, the procedures that were employed to compute the $\underline{r}^2$ of .09 are in need of a statistical explanation and rationale.

In addition, it would seem that something could be said about the difference between the $\underline{\eta}^2$ (.20) provided by the between-groups analysis and the $\underline{r}^2$ (.09) provided by the procedure above. For example it would appear intuitively straightforward that technological complexity does not account for all the situationally related variation in perceptions of job challenge, given that .09 is less than .20. Here again, however, a statistical rationale is needed for comparing the $\underline{r}^2$ with $\underline{\eta}^2$.

The remainder of this article is devoted to the development of a statistical rationale for relating a PV with a continuously distributed situational variable. Because this is a relatively new area in need of explication, it was considered appropriate to begin the derivations with basic regression equations using unstandardized variables, and then proceed to the use of standardized variables (beta-weights and correlations). An important difference between standardized and unstandardized regression weights will be demonstrated. Second, as a direct result of the derivations included in the statistical rationale, a method is presented for the comparison and interpretation of differences between $\underline{\eta}^2$ and the squared PV - situational variable correlation. Finally, univariate procedures are extended to the multivariate case, and an empirical example is presented.

Statistical Rationale

For illustrative purposes, the following conditions were assumed:

(1) $\underline{S_i}$ is a situational variable, on which each of $\underline{k}$ groups has a unique score ($\underline{i}$ = 1,2...$\underline{k}$), although some groups

may have the same score as other groups. When all individual members of the *same* group are assigned the (same) value of S_i for that group, the designator S_{ij} is used, where j represents the j^{th} individual in a group comprised of n_i individuals ($j = 1,2,...n_i$). Statistically, it is simpler to express *individuals'* scores on S_i in grand-mean deviation form. Thus, $s_{ij} = S_{ij} - \sum_i \sum_j S_{ij}/N$, where N represents the total number of individuals ($\sum_i n_i = N$). Note that with grand-mean deviation scores, $\sum_i n_i s_i = 0$. The variance of the s_{ij} in the total sample, $\sigma^2_{s_{ij}}$, is $(1/N)(\sum_i n_i s_i^2)$, which can also be written as $\sigma^2_{s_i}$ since all s_{ij} in the same group i are the same.

(2) Y_{ij} is the j^{th} individual's score in the i^{th} group on the person variable (PV). Note especially that the Y_{ij} are not constrained to be equal for all n_i individuals in the i^{th} group. In grand-mean deviation form (i.e., $y_{ij} = Y_{ij} - \sum_i \sum_j Y_{ij}/N$):

(a) $\sum_i n_i \bar{y}_i = 0$, where $\bar{y}_i = \sum_j y_{ij}/n_i$ or the mean y_{ij} for group i;

(b) $\sigma^2_{y_{ij}} = (1/N)(\sum_i \sum_j y_{ij}^2)$, the variance for the total sample of y_{ij} scores; and, (c) $\sigma^2_{\bar{y}_i} = (1/N)(\sum_i n_i \bar{y}_i^2)$, the variance of the weighted group mean y_{ij}s.

With this information, the linear model for regressing a PV (the y_{ij}s) on a situational variable, represented by s_{ij}, is as follows:

$$y_{ij} = b_{ys}\ s_{ij} + e_{ij} \qquad (1)$$

where b_{ys} is an unstandardized regression weight, e_{ij} is the ordinary least squares (OLS) error term, and the equation is based on the total sample of individuals.

Because s_{ij} is the same for all individuals in group i, Equation 1 can also be written as

$$y_{ij} = b_{ys}\ s_i + e_{ij} \qquad (2)$$

To solve for b_{ys}, one can multiply through Equation 2 by s_i and then sum across j and i, as shown below.

$$\sum_i \sum_j y_{ij}\ s_i = b_{ys} \sum_i \sum_j s_i^2 + \sum_i \sum_j e_{ij}\ s_i \qquad (3)$$

However, $\sum_i \sum_j e_{ij}\ s_i = 0$ given the properties of OLS. Thus, Equation 3 takes the form

$$b_{ys} = (\sum_i \sum_j y_{ij}\ s_i)/(\sum_i \sum_j s_i^2)$$

$$= (\sum_i \sum_j y_{ij}\ s_i)/(\sum_i n_i\ s_i^2) \qquad (4)$$

$$= \sigma_{y_{ij}s_i}/\sigma^2_{s_i} \quad \text{(when scaled by } 1/N\text{)} \qquad (5)$$

where $\sigma_{y_{ij}s_i}$ is a covariance term.

It is also the case that $\sum_i \sum_j y_{ij} = \sum_i n_i\ \bar{y}_i$; that is, $\sum_j y_{ij}/n_i = \bar{y}_i$. When this rationale is applied to Equation 4, Equation 5 may be depicted as

$$\sigma_{\bar{y}_i s_i}/\sigma^2_{s_i} \qquad (6)$$

thus connoting that $\sigma_{y_{ij}s_i} = \sigma_{\bar{y}_i s_i}$

This result provides the important conclusion that when Equation 2 is summed on *j*, and is multiplied by $1/n_i$,

$$\bar{y}_i = b_{ys}\, s_i + \bar{e}_i = b_{\bar{y}s}\, s_i + \bar{e}_i$$

thus, $b_{ys} = b_{\bar{y}s}$. That is, the unstandardized regression weights are the *same* for predicting the separate y_{ij} and the mean y_{ij} (i.e., $\bar{y}_i$) for each group.

If the variables are standardized, the above equality generally does *not* hold for beta-weights. That is, β_{ys} is not generally equal to $\beta_{\bar{y}s}$. In the bivariate case, beta weights are correlation coefficients and thus the equations will be expressed in terms of correlations. Expressing correlations in terms of covariances, and using the equations for covariances derived above, we have the following

$$r_{y_{ij}s_i} = r_{ys} = \sigma_{y_{ij}s_i}/(\sigma_{y_{ij}}\ \sigma_{s_i})$$

$$= \sigma_{\bar{y}_i s_i}/(\sigma_{y_{ij}}\ \sigma_{s_i}) \tag{7}$$

while,

$$r_{\bar{y}_i s_i} = r_{\bar{y}s} = \sigma_{\bar{y}_i s_i}/(\sigma_{\bar{y}_i}\ \sigma_{s_i}) \tag{8}$$

Note that Equations 7 and 8 include the terms $\sigma_{y_{ij}}$ (Equation 7) and $\sigma_{\bar{y}_i}$ (Equation 8) in the denominators, which can generally be assumed to be unequal given that the PV -- y_{ij} -- would usually be expected to vary among individuals in the *same* group (cf. James et al., 1978).

From Equations 7 and 8, it is seen that r_{ys}, the correlation between a PV and a situational variable, when correlated over the total sample of individuals, is

$$r_{ys} = \frac{\sigma_{\bar{y}_i}}{\sigma_{y_{ij}}} r_{\bar{y}s} \tag{9}$$

or,

$$r^2_{ys} = \frac{\sigma^2_{\bar{y}_i}}{\sigma^2_{y_{ij}}} r^2_{\bar{y}s} \tag{10}$$

Furthermore, $\sigma^2_{\bar{y}_i}/\sigma^2_{y_{ij}}$ is η^2_y, the correlation ratio (eta-square) of y_{ij} on group membership. Thus, Equation 10 is

$$r^2_{ys} = \eta^2_y \, r^2_{\bar{y}s} \tag{11}$$

where r^2_{ys} is the proportion of the variance in a PV associated with a particular situational variable s_i; η^2_y is the total amount of variation in the PV that is associated with between-group differences; and $r^2_{\bar{y}s}$ is the variance in the weighted group mean PV scores that is associated with differences in the situational variable s_i.

Viewed from another perspective, η^2_y is the maximum possible variation in the PV that is associated with between-group differences. r^2_{ys} will be equal to η^2_y only in the condition that $r^2_{\bar{y}s} = 1.0$, which can be seen in Equation 11. Note that $r^2_{\bar{y}s}$ will be less than 1.0, and therefore $r^2_{ys} < \eta^2_y$, when (a) the relationship between the $\bar{y}_i$ and s_i is nonlinear, and/or (b) between-group variation exists in the y_i that is not associated with

s_i (see Equation 8). Assuming relationships to be *linear*, which can be checked empirically, we see that $r^2_{\bar{y}s}$ represents the proportion of variation in η^2_y that is included in r^2_{ys}. In other words, $r^2_{\bar{y}s}$ indicates the degree to which the obtained r^2_{ys} approaches the maximum possible variation in a PV associated with between-group differences. This is seen simply by converting Equation 11 to

$$\frac{r^2_{ys}}{\eta^2_y} = r^2_{\bar{y}s} \tag{12}$$

To summarize, it has been shown that the unstandardized regression weights are equivalent when a continuously distributed situational variable is employed to predict either individual scores on a PV or weighted, group mean scores on a PV. Such equivalence does not hold for standardized regression weights, which in the bivariate case are correlation coefficients. It was also shown that the squared correlation between a continuously distributed situational variable and a PV could be decomposed into (a) an eta-square, which is the maximum variation in a PV associated with between-group differences, and (b) the squared correlation between the weighted group means on the PV and the situational variable ($r^2_{\bar{y}s}$). This decomposition has the important implication that, assuming linearity, $r^2_{\bar{y}s}$ reflects the degree to which the obtained r^2_{ys} approaches the maximum variation in a PV associated with between-group differences, as measured by η^2_y.

A straightforward use of this information would be to ascertain whether additional variables should be added to a

study in the interest of accounting for reliable variance that still remains between-groups. That is, $1 - r_{\bar{Y}s}^2$ indicates the proportion of between-group variation in the PV that is not accounted for by the situational variable S_i. Note that such variance need not be strictly situational. As addressed earlier, some part of between-group variation might reflect mean group differences in age, education, experience, ability, etc., which suggests that these variables would be meaningful candidates for inclusion in the analyses (in group-mean form).

The preceding logic extends directly to multiple regression analyses based on two or more S_i variables which have the same values for all individuals in each group. Thus, the unstandardized regression weights are the same in value for predicting either the y_{ij} or the $\bar{y}_i$. On the other hand, the standardized regression weights or beta-weights are generally not the same, and, analogically with Equation 9, the relationship between the weights is $\beta_{Ys} = \eta_Y \beta_{\bar{Y}s}$. Similarly, the squared multiple correlations are related by $R_Y^2 = \eta_Y^2 R_{\bar{Y}}^2$, where R_Y^2 represents the squared multiple correlation between one PV and two or more continuously distributed situational variables. Using the same logic as above, $R_{\bar{Y}}^2$, the squared multiple correlation between the weighted group means on the PV and the situational variables, indicates the degree to which R_Y^2 approaches the maximum variation in the PV that is associated with between-group differences, as reflected by η_Y^2.

An Illustration

To illustrate the use of the above rationale, one set of data was selected from an ongoing research study (Hater, Note 1). The data include (a) subordinates' perceptions of interdepartmental conflict ($\underline{y}_{ij}$) on the part of the 124 high level, technical personnel in an information systems department in a private health care foundation (e.g., systems analysts); and (b) measures of workgroup centralization of decision making ($\underline{s}_{1i}$, where the first subscript connotes situational variable number) and workgroup formalization of work roles ($\underline{s}_{2i}$), where separate measures of $\underline{s}_{1i}$ and $\underline{s}_{2i}$ were obtained for each of the 19 workgroups in which the 124 subordinates were employed (workgroup supervisors provided the $\underline{s}_{1i}$ and $\underline{s}_{2i}$ scores). A one-way ANOVA, using the 19 workgroups as the independent variable (classification factor) and the perceptions of interdepartmental conflict as the dependent variable, resulted in an $\eta_{\underline{y}}^2$ of .26 ($\underline{p}<.05$). This connotes that 26% of the variance in perceptions of interdepartmental conflict was associated with between-group variations in the 19 workgroups.

The squared correlations between the two situational variables and perceptions of interdepartmental conflict are presented in column one of Table 1 under univariate analysis (i.e., the $\underline{r}_{ys}^2$ column). Following prior discussion, the correlations were computed by assigning each individual in group $\underline{i}$ ($\underline{i}$ = 1 ... 19) the same $\underline{s}_{1i}$ and $\underline{s}_{2i}$ scores, and then correlating the $\underline{y}_{ij}$ and $\underline{s}_{1i}$ and $\underline{s}_{2i}$ scores on the total (i.e., across group) subordinate sample. Before squaring, the correlations

Table 1

Relationships Between Subordinates' Perceptions of Interdepartmental Conflict and Centralization of Decision-Making and Formalization of Work Roles

	Univariate Analysis	
Situational Variables	r^2_{ys}	$r^2_{\bar{y}s}$
Centralization of Decision Making (s_{1i})	.05*	.19
Formalization of Work Roles (s_{2i})	.07**	.27
	Multivariate Analysis	
	R^2_y	$R^2_{\bar{y}}$
s_{1i} ; s_{2i}	.10**	.38

Note. All analyses based on individual subordinate sample (N = 124).

*p < .05

**p < .01

were significant and positive. The positive correlations suggest that individuals in high level technical jobs, which require a certain degree of flexibility, autonomy, and boundary-spanning, are likely to perceive a lack of cooperation and more conflict among organizational departments when decision-making processes are constrained by centralized and formalized structures (cf. James & Jones, 1976).

The $r^2_{\bar{Y}s}$ column in Table 1 under univariate analysis indicates the proportion of total variation in subordinates' perceptions of interdepartmental conflict associated with between-group differences that was accounted for by either centralization or formalization (the relationships were linear). For example, centralization of decision making accounted for 19% of that variance in interdepartmental conflict that was associated with between-group differences. Consequently, 81% of the variance in the perceptions that was associated with between-group differences was not accounted for by centralization (i.e., $1 - r^2_{\bar{Y}s}$). It is important to note that $r^2_{\bar{Y}s}$ need not be calculated directly. One only needs to calculate η^2_Y, each r^2_{Ys}, and then divide each r^2_{Ys} by η^2_Y (see Equation 12).

The lower part of Table 1 presents the results of the multiple correlation analysis. Disaggregated centralization and formalization were correlated .30 (N = 124 subjects, $p<.01$); this connotes that the values of the $r^2_{\bar{Y}s}$ s from the univariate analysis could not simply be added to obtain an estimate of variance attribution. The squared multiple correlation, R^2_Y, again computed on the subordinate sample, was .10 ($p<.01$).

Division of R_Y^2 by η_Y^2, which provided $R_{\bar{Y}}^2$, was .38 (i.e., .10/.26), suggesting that 38% of the variation in subordinates' perceptions of interdepartmental conflict that was associated with between-group differences was accounted for by a linear combination of centralization and formalization.

Since the relationships among the variables were linear, the results of the analysis above indicate clearly that additional between-group predictors are needed in the study. That is, based on 1 - $R_{\bar{Y}}^2$, 62% of the between-group variation in the perceptions remains to be accounted for. It is believed that this is important information. It should be noted that in practice the differences between η_Y^2 and R_Y^2 may reflect nonlinearity, in which case various forms of polynominal regression or moderator analysis might be indicated (see Sockloff, 1976a, 1976b, 1977, however, before proceeding with these types of analyses).

Two final points deserve mention. First, the illustration dealt only with correlations. This seemed appropriate in that correlations communicate readily, in an easily interpretable format, the results of statistical analyses. However, occasions exist in which correlations and beta-weights should not be employed (cf. Tukey, 1964), and the use of unstandardized regression weights is preferred. Unstandardized regression weights are also useful because of the equality discussed previously. However, it is also the case that a rather simple basis for computing variance attributions, such as presented in Table 1, is not easily developed or interpreted for unstandardized regression weights. Consequently, it would

appear that correlational forms of analysis, when justified, provide more useful information in this particular case. Nevertheless, an understanding of the underlying statistical rationale associated with both unstandardized and standardized regression weights is certainly worthwhile before attempting to employ the procedures outlined.

Second, a note of caution needs to be offered concerning the number of situational variables in relation to the number of groups. Ordinarily there should be many more groups than situational variables. When this is not the case, the interpretation of results must be guarded. For example, if there were only two groups, a single situational variable whose value differs for the two groups would serve as an identifier of group membership and would account fully for the between-group variation of a PV, irrespective of whatever conceptual meaning might be deserved otherwise for the situational variable. In general, if there are $\underline{k}$-1 situational variables (where $\underline{k}$ is the number of groups), and none of these variables can be perfectly predicted linearly by one or more of the remaining situational variables, $R^2_{\bar{Y}}$ will always be equal to 1.00. In such a case the set of situational variables merely serves to identify group membership and will always yield $R^2_Y = \eta^2_Y$ and thus $R^2_{\bar{Y}} = 1.0$. The same would be true for a set of randomly generated situational variables (cf. Cohen & Cohen, 1975), and thus it should be clear that as the number of situational variables ($\underline{p}$) approaches or reaches the number of groups minus one ($\underline{k}$-1), the closeness of R^2_Y to η^2_Y has lesser relevance

to the substantive import of the situational variables and more relevance to their role as identifiers of group membership. The foregoing is of little concern when the number of groups is very large in comparison to the number of situational variables, but in some studies this may not be the case.

One approach to the problem just described is to estimate the value of $R_{\underline{Y}}^2$ in the population (where $\underline{k}$ is infinitely large). A formula for such an estimate (Wherry, 1931) is

$$\hat{R}_{\underline{Y}}^2 = 1 - \frac{\underline{k}-1}{\underline{k}-\underline{p}-1}\,(1-R_{\underline{Y}}^2)\ ,$$

where

$\hat{R}_{\underline{Y}}^2$ is an estimate of the proportion of $\eta_{\underline{Y}}^2$ due to the situational variable(s) apart from being mere identifiers of group membership; this also is an estimate of the population value of $R_{\underline{Y}}^2$, albeit a biased estimate, but not seriously so (Montgomery & Morrison, 1973).

In practice the number of situational variables usually will not be large (i.e., $\underline{p} \leq 10$). The results given in Table 2 illustrate the use of the Wherry formula in such cases. That is, shown in Table 2 are the values of $\hat{R}_{\underline{Y}}^2$ for various values of $R_{\underline{Y}}^2$ for $\underline{p}$ between 2 and 10 and for $\underline{k}$ equal to either 10 or 20 groups. As can be seen, the proportion of the between-group variance ($\eta_{\underline{Y}}^2$) attributable to the $\underline{S}$ variables, apart from their role as identifiers of group membership, shows marked variations. As a rule of thumb, when $R_{\underline{Y}}^2 \leq .50$ and $\underline{k} \leq .50\underline{p}$,

Table 2

Estimated Population Values of $R^2_{\bar{Y}}$ for Given Sample Values, Based on Differing Numbers of Situational (S) Variables and Either 10 or 20 Groups

No. of S Variables	.30	.40	.50	.60	.80	.90
			Sample Values of $R^2_{\bar{Y}}$			
10 Groups						
2	.10	.23	.36	.49	.74	.87
4	0	0	.10	.28	.64	.82
6	0	0	0	0	.40	.70
8	0	0	0	0	0	.10
20 Groups						
2	.22	.33	.44	.55	.78	.89
4	.11	.24	.37	.50	.75	.87
6	0	.12	.27	.42	.71	.86
8	0	0	.14	.31	.65	.83
10	0	0	0	.16	.48	.79

Note. Negative estimated values were set to 0.

no conceptual meaning should be attributed to the variance accounted for by the situational variables. This does not imply that these variables do not carry such a meaning, but rather that the data at hand do not support such an interpretation.

Conclusions

Two primary goals of this explication were (a) to encourage researchers to develop meaningful and specific measures of situational (environmental) attributes, and (b) to present a statistical rationale for relating situational variables with person variables. A method was provided to ascertain the degree to which an obtained r_{ys}^2 (R_y^2) approaches the maximum possible variation in a PV associated with between-group differences. It was noted further that between-group variation not accounted for could be associated with other situational attributes, other individual attributes (e.g., group-mean differences in age), and nonlinear effects.

Several cautions should also be mentioned. First, with purely correlational data, it is generally unwise to attempt to infer that the variance attributions (η_y^2, r_{ys}^2, $r_{\bar{y}s}^2$, R_y^2, $R_{\bar{y}}^2$) are causal. For example, it may be that individual behaviors have affected causally the situational variables (cf. Bandura, 1978; Endler & Magnusson, 1976; James et al., 1978). To address this type of question with correlational data, the researcher might wish to employ various statistical procedures that address causality, such as cross-lagged panel correlation, path analysis, or structural equation procedures (cf. Duncan, 1975; James & Singh, 1978; Kenny, 1975).

Second, caution should be used when the situational variables are based on aggregates of individual scores. Not only should a defense be provided for interpreting the aggregates at the situational level, but various forms of interpretative bias (e.f., ecological fallacy) should be avoided (Firebaugh, 1978; Hannan, 1971, 1974; James & Jones, 1974; Robinson, 1950)[2].

Finally, with the exception of η_{Y}^{2}, we have focused exclusively on continuously distributed situational variables, which reflects our bias toward the use of parametric procedures whenever possible. However, the rationale developed is equally applicable to categorical variables, where, for example, a situational variable is operationalized in terms of different types of training received. In this case, R_{Y}^{2} is determined by the use of well-known dummy variable procedures (Cohen & Cohen, 1975), or perhaps a mix of dummy variables and continuously distributed variables, and the relationship $R_{Y}^{2} = \eta_{Y}^{2} R_{\bar{Y}}^{2}$ is applicable.

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[2]It is also worth reiterating that the results of the analyses described in this article should be interpreted only at the individual level of analysis.

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